

Review

A systematic review of machine learning-based microscopic traffic flow models and simulations

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ABSTRACT

Microscopic traffic flow models and simulations are crucial for capturing vehicle interactions and analyzing traffic. They can provide critical insights for transport planning, management, and operation through scenario testing and optimization. With the growing availability of high-resolution data and rapid advancements in machine learning (ML) techniques, ML-based microscopic traffic flow models are emerging as promising alternatives to traditional physical models, offering improved accuracy and greater flexibility. Although many models have been developed, comprehensive studies that critically assess the strengths and weaknesses of these models and the overall ML-based approach are lacking. To fill this gap, this study presents a systematic review of ML-based microscopic traffic flow models and simulations, covering both car-following and lane-changing behaviors. This review identifies key areas for future research, including the development of methods to improve model transferability across different operational design domains, the need to capture both driver-specific and location-specific heterogeneity via benchmark datasets, and the incorporation of advanced ML techniques such as meta-learning, federated learning, and causal learning. Additionally, enhancing model interpretability, accounting for mesoscopic and macroscopic traffic impacts, incorporating physical constraints in model training, and developing ML models designed for autonomous vehicles are crucial for the practical adoption of ML-based microscopic models in traffic simulations.

Nomenclature

ADAS	Advanced driver assistance systems	LCD	Lane-changing decision
ACC	Adaptive cruise control	LCE	Lane-changing execution
ANN	Artificial neural network	LCI	Lane-changing impact
AV	Autonomous vehicle	LightGBM	Light gradient boosting machine
BI	Bayesian inference	LIME	Local interpretable model-agnostic explanation
BN	Bayesian network	LSTM	Long short-term memory
CAV	Connected and autonomous vehicle	LV	Leading vehicle in the current lane
CF	Car-following	ML	Machine learning
CNN	Convolutional neural network	MoE	Mix of expert
DBN	Deep belief network	NP	Neural process
ET	Extra tree	NGSIM	Next generation simulation
FFNN	Feed-forward neural network		

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FL	Federated learning	ODD	Operational design domain
FTL	Federated transfer learning	PIDL	Physics-informed deep learning
FV	Following vehicle in the current lane	RF	Random forest
GAM	Generalized additive model	RL	Reinforcement learning
GAN	Generative adversarial network	RNN	Recurrent neural network
GAIL	Generative adversarial imitation learning	RUSBoosted	Random under-sampling boosted
GMM	Gaussian mixture model	seq2seq	Sequence-to-sequence
GMR	Gaussian mixture regression	SHAP	Shapley additive explanations
GRU	Gated recurrent unit	SVM	Support vector machine
HMM	Hidden markov model	SV	Subject vehicle
HV	Human-driven vehicle	TTC	Time to collision
IDM	Intelligent driver model	TF	Following vehicle in target lane
IRL		TL	Leading vehicle in target lane

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	Inverse reinforcement learning		
ITS	Intelligent transport system	V2V	Vehicle to infrastructure
k-NN	k-nearest neighbor	V2V	Vehicle to vehicle
LC	Lane-changing	V2X	Vehicle to everything
		XGBoost	Extreme gradient boosting

1. Introduction

Microscopic simulation is widely used in practice for understanding complex traffic scenarios, offering cost-effective and adaptable solutions for assessing new technologies and interventions through scenario testing and optimization (Nor Azlan and Md Rohani, 2018; Sohel Mahmud et al., 2019). These simulations are based on car-following (CF) and lane-changing (LC) models, which describe the two primary driving tasks (Zheng et al., 2014). To develop realistic simulations, it is crucial to calibrate and validate the models with real-world data so that the simulations are fit for purpose and applicable across all operational domains within the simulation framework (Park and Schneeberger, 2003). For this purpose, an increasing number of real-world trajectory-level datasets are now available, such as next generation simulation (NGSIM) (U.S. Department of Transportation, 2020), highD (Krajewski et al., 2018), SPMD (Safety Pilot Model Deployment Data – Catalog, 2020), SHRP2 (SHRP2 NDS Data Access, 2020), and autonomous vehicle (AV) datasets, such as OpenACC (Makridis et al., 2021) and Waymo (Hu et al., 2022).

The availability of these trajectory-level datasets and the rapid advancement of machine learning (ML) techniques have led to a proliferation of ML-based CF and LC models in recent years, hereafter referred to as ML-CF models and ML-LC models, respectively. ML-CF models mostly use artificial neural networks (ANN)-based models to predict the behavior of a subject vehicle (SV) in future time steps on the basis of historical data from both the SV and the leading vehicle (LV) (Fang et al., 2022; Pan et al., 2023; Zhou et al., 2022). On the other hand, ML-LC models use a wider range of modeling methods, including regression-based and classifier techniques. The ML-CF and ML-LC models are trained directly on real-world data, eliminating the need for explicit calibration of predefined parameters. This approach offers greater flexibility and allows the incorporation of multiple features within the model. In contrast to ML-based models, traditional physical CF and LC models struggle to capture more complex driving behaviors because of their reliance on predetermined structures and parameters (Saifuzzaman and Zheng, 2014; Zheng et al., 2014). Notably, compared with their traditional counterparts, ML-CF models have demonstrated superior accuracy in replicating microscopic following trajectories (Papathanasopoulou and Antoniou, 2015; Yan and Zhou, 2021; Zhou et al., 2017). Likewise, ML-LC models have shown improvements in predicting LC behaviors (Griesbach et al., 2022; Liu et al., 2020a; Zhang et al., 2019).

While some recent reviews have shed light on specific facets of ML applications within microscopic simulations, they have focused mostly on isolated topics such as AVs, CFs, or LCs and without a holistic overview of the ML models employed. For example, Zhang et al. (2024) reviewed traditional and ML-CF modeling approaches for human-driven vehicles (HVs), and Ahmed et al. (2021) and Sadid and Antoniou (2023) considered CF modeling of AVs, all of which lacked a review of LC behavior. Conversely, Rahman et al. (2013), David and Söffker (2023), Liu et al. (2023), and Ma and Li (2023) provided a review of the traditional and ML-LC literature on HVs, whereas Bevely et al. (2016) investigated LC modeling for AVs, none included CF behavior. Gora et al. (2020) offered a review of microscopic traffic modeling of AVs, without any mention of ML techniques, and Papathanasopoulou et al. (2018) provided insights into the data-driven advancements in both mesoscopic traffic models and microscopic driving models within simulation contexts, without exploring diverse CF and LC modeling techniques. While

these reviews have provided valuable insights into specific aspects of ML-based microscopic model development, comprehensive studies that critically assess the strengths and weaknesses of diverse ML models and the overall ML-based approach are lacking. Furthermore, this can hinder our understanding of how ML approaches can optimize both CF and LC models in a unified manner and develop robust, generalizable traffic models capable of adapting to diverse scenarios.

To address this gap, our systematic review offers the first comprehensive study of the state-of-the-art in ML-CF and ML-LC model development. In doing so, we make three key contributions to the field. First, we provide a holistic overview of the ML methodologies employed for both CF and LC, which can shed light on the development of unified models. Second, we discuss diverse approaches to model training. We analyze how different training strategies can enhance both model performance and applicability and demonstrate the importance of input data feature selection and engineering in improving model accuracy. Finally, we offer recommendations for future research directions, including enhancing model transferability across operational domains, enhancing model interpretability, capturing mesoscopic and macroscopic traffic impacts, integrating physical constraints in model training, and developing ML-based models for AVs.

The subsequent sections of this paper are organized as follows. Section 2 outlines the review methodology employed in our systematic review. Sections 3 and 4 provide an in-depth review of the ML-CF and ML-LC models, respectively. Section 5 recommends future research directions to address the gaps identified in the review, and Section 6 presents the conclusion.

2. Method

This systematic review covers ML-CF and ML-LC models developed from real-world data. It adheres to the guidelines outlined in the preferred reporting items for systematic reviews and meta-analyses (PRISMA) framework (Liberati et al., 2009). An overview of our literature search methodology is provided in Table 1.

While we cover models developed for capturing AV driving behavior, these models should not be confused with research centered on control strategies (Chakraborty et al., 2022; Li and Shrivastava, 2002; Li et al., 2018; Lu and Aakre, 2018; Tang et al., 2022; Zhang et al., 2022a) or path planning (Zhou et al., 2020) of AVs. Additionally, research that considers physiological indicators from drivers is excluded from this review, including parameters such as the respiration rate (Gao et al., 2018a; Wang et al., 2016), the driver's vision angle (Deng et al., 2020; Leonhardt and Wanielik, 2017; Peng et al., 2015; Zhou et al., 2017), and head rotation (Wei et al., 2021), as our review focuses on the behaviors of vehicles and traffic patterns rather than the physiological behaviors of drivers. A total of 56 CF and 104 LC papers that adhered to the prescribed criteria were identified and selected for detailed review. Table 2 provides numbered references for each of the reviewed papers. These number references are used in square brackets in subsequent figures.

A comprehensive analysis of keywords from each paper was conducted to discern recurring themes and areas of investigation. The network visualizations in Fig. 1 offer insights via keyword analysis, indicating the frequency of keywords and connections between keywords and ML methodologies. For clarity, certain redundant keywords, such as machine learning, artificial intelligence, lane-changing, or car-following, were left out, and synonymous keywords were combined. If keywords were not provided by the paper, relevant keywords were extracted from the paper's title and abstract to ensure full coverage of all reviewed papers.

From the keyword analysis, autonomous vehicles emerged as the most prevalent term in both the CF and LC papers, alongside related terms such as Adaptive Cruise Control, Intelligent Transport Systems (ITS), and Advanced Driver Assistance Systems (ADAS). This underscores the importance of AV deployment as a relevant use case for ML models. Hence, we explore how ML models can be further enhanced to capture

evolving AV behaviors and modelling requirements in our future directions section. The CF literature regularly explores mesoscopic patterns, as evidenced by frequent mentions of terms such as congestion, hysteresis, oscillation, and stability analysis. LC papers tend to emphasize data preprocessing aspects, highlighted by terms such as feature selection, clustering, prefiltering, and Bayesian filtering. CF papers predominantly leverage ANNs and recurrent neural networks (RNNs), particularly long short-term memory networks (LSTMs) and gated recurrent units (GRUs), incorporating advanced ML techniques such as attention mechanisms, sequence-to-sequence (seq2seq) models, and adversarial learning, whereas LC papers exhibit a broader spectrum of ML methodologies, including ensemble learning, with more comparative research between methods.

Our review also consolidates the key real-world trajectory-level datasets commonly used to develop and validate the models. Each dataset provides unique insights into driving behavior, facilitating a wide range of applications in model development, autonomous vehicles (AVs), and safety analysis. The NGSIM offers detailed vehicle trajectory data on multilane freeways and arterials, capturing positions, speeds, accelerations, and lane changes. Similarly, HighD provides drone-captured trajectories on multilane freeways, including vehicle positions, speeds, and proximity indicators, enabling multivehicle behavior modeling. The SPMD dataset captures vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications through basic safety messages, which include vehicle position, motion, and safety-related data. This dataset is collected on freeways and urban roads—including intersections—and supports the integration of V2V and V2I communications in traffic modeling. OpenACC focuses on adaptive cruise control (ACC) scenarios, capturing both track and real-world trials with varying platoon lengths. This dataset includes information on vehicle speed, spacing, and headway time, which is specifically tailored to AV driving scenarios. The Waymo Open dataset contains 20-s sequences of high-resolution sensor data from level 4 AVs in suburban and urban environments. It features lidar, camera, and radar data, along with 3D object labels and an environmental context, supporting research on machine perception and AV

technologies. Preprocessing is required to extract trajectory data such as speeds and gap distances (Hu et al., 2022). Together, these datasets offer a comprehensive set of features essential for advancing research in ML-based microscopic traffic flow models.

3. Machine learning-based car-following (ML-CF) models

Traditional CF models have been studied for more than 70 years (Pipes, 1953) and include many approaches, such as stimulus-response, safety distance, linear, and psychophysical methods (Brackstone and McDonald, 1999). These models are grounded in mathematical rules and incorporate physical parameters, such as the desired speed v_0 and maximum acceleration a , ensuring interpretable results and physically realistic behaviors, such as collision avoidance. In contrast, ML-CF models are nonparametric models that forecast the future movements of the SV relative to its leader to replicate real-world CF dynamics via trajectory data. Unlike traditional CF models, ML-based models rely on factors such as advanced ML algorithms, input feature selection, and suitable training methodologies to increase model accuracy and applicability. Fig. 2 provides a breakdown of the data and types of features used for the training and validation of the ML-CF models. Notably, the NGSIM freeway dataset is the most frequently employed dataset. To date, most ML-CF models focus on HV behavior rather than AV behavior, primarily due to the abundance of HV datasets. Additionally, most ML-CF models are trained via local feature training, with only a handful using trajectory or mesoscopic features.

Typically, ML-CF models predict a single output for a single future timestep for the SV, for example, speed $v_{SV}(t)$, acceleration $a_{SV}(t)$, or following distance $s_{SV}(t)$, with $a_{SV}(t)$, being the most frequently predicted output, followed by $v_{SV}(t)$ and then $s_{SV}(t)$. Some models predict multiple outputs over a time sequence, i.e., seq2seq models (Fang et al., 2022; Lin et al., 2022; Lu et al., 2023; Ma and Qu, 2020; Wang et al., 2023). These output features are all physically interrelated, and there is no strong evidence to suggest that predicting a particular output feature is inherently superior to predicting another.

Table 1
Framework for the systematic review of the ML-CF and ML-LC model literature.

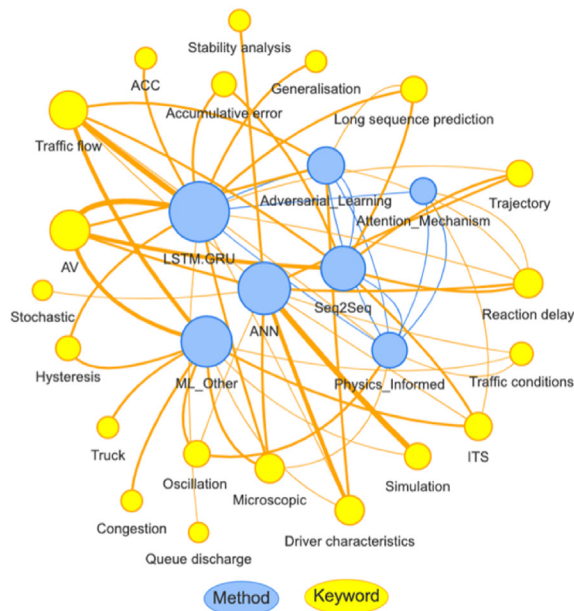
Identification of studies from scopus and google scholar		
Identification	Car-following model	Lane-change model
	Search: Title, Abstract, Keywords: 'data-driven' or 'machine learning' or 'ML' or 'nonparametric', AND 'car-following' or 'microscopic driving' or 'behavioral model' or 'trajectory prediction' $n^* = 247$	Search: Title, Abstract, Keywords: 'data-driven' or 'machine learning' or 'ML' or 'nonparametric', AND 'lane-changing' or 'cut-in' or 'merge' or 'diverge' or 'maneuver recognition' or 'microscopic driving' or 'behavioral model' or 'trajectory prediction' $n = 413$
Additional research identified from paper citations ($n = 22$)		
Screening	Duplicate removal and high-level screening of titles and abstracts.	
	<u>Each paper to contain:</u> One of more car-following models developed using ML techniques $n = 74$	<u>Each paper to contain:</u> One or more lane-changing decision, execution or impact models developed using ML techniques $n = 158$
Eligibility	Further screening	
	<u>Eligibility criteria:</u> Source data: Model must be based on real-world data (can include data from simulator and AVs). If an ML-CF or ML-LC model is developed as part of a driving system (Wu et al., 2016; Vallon et al., 2017), the ML-CF or ML-LC component will be considered in this review. Exclusion: Models without real-world validation (e.g., Wei et al., 2013). Exclusion: Driver physiological features. Exclusion: Control strategies or path planning of AVs.	
Included	$n = 56$ research papers, each with one or more ML-CF models developed. Refs: [1–56]	$n = 104$ research papers, each with one or more ML-LC models developed. Refs: [51, 57–159]

Note: n refers to the number of papers included at each stage.

Table 2

All the ML-CF and ML-LC papers identified for this review.

#	Ref.	#	Ref.	#	Ref.	#	Ref.
Car-following							
1	Hongfei et al. (2003)	15	Zhu et al. (2018)	29	Yan and Zhou (2021)	43	Wang et al. (2023)
2	Panwai and Dia (2007)	16	Gao et al. (2018b)	30	Colombaroni et al. (2021)	44	Lu et al. (2023)
3	Chong et al. (2011)	17	Hao et al. (2018)	31	Soldevila et al. (2021)	45	Pan et al. (2023)
4	Khodayari et al. (2012)	18	Li et al. (2019)	32	Liao et al. (2022a)	46	Wen et al. (2023)
5	Zheng et al. (2013)	19	Sun et al. (2019)	33	Xu et al. (2022)	47	Yu et al. (2023)
6	Wei and Liu (2013)	20	Yang et al. (2019a)	34	Zhu et al. (2022)	48	Liu et al. (2023)
7	Aghabayk et al. (2014)	21	Tang et al. (2020)	35	Lin et al. (2022)	49	Yang et al. (2023)
8	Colombaroni and Fusco (2014)	22	Ma and Qu (2020)	36	Liu et al. (2022)	50	Adewale and Lee (2023)
9	Papathanasopoulou and Antoniou (2015)	23	Zhou et al. (2020)	37	Zhou et al. (2022)	51	Chen et al. (2023)
10	He et al. (2015)	24	Gu et al. (2020)	38	Raveendran et al. (2022)	52	Ma et al. (2023)
11	Morton et al. (2017)	25	Xie et al. (2020)	39	Fang et al. (2022)	53	Kinoshita and Shiomi (2023)
12	Zhou et al. (2017)	26	Mo et al. (2021)	40	Zou et al. (2022)	54	Qin et al. (2023)
13	Wang et al. (2018)	27	Shi et al. (2021)	41	Mo and Di (2022)	55	Ma and Qu (2023)
14	Huang et al. (2018a)	28	Harth et al. (2021)	42	Zhang et al. (2022b)	56	Davies et al. (2024)
Lane-changing							
57	Mandalia and Salvucci (2005)	83	Li et al. (2018)	109	Song (2021)	135	Ardakani and Bonds (2023)
58	Berndt et al. (2008)	84	Monot et al. (2018)	110	Das and Ahmed (2021)	136	Gao et al. (2023)
59	Kasper et al. (2011)	85	Ren et al. (2019)	111	Gallitz et al. (2021)	137	Zhang et al. (2023)
60	Kumar et al. (2013)	86	Liu et al. (2019a)	112	Shi and Zhang (2021)	138	Tomar et al. (2010)
61	Hou et al. (2014)	87	Weidl et al. (2018)	113	Wang et al. (2021)	139	Tomar et al. (2011)
62	Schlechtriemen et al. (2015)	88	Wei et al. (2019)	114	Abraham et al. (2021)	140	Ding et al. (2013)
63	Park et al. (2015)	89	Gu et al. (2019)	115	Li et al. (2021)	141	Yao et al. (2013)
64	Rehder et al. (2016)	90	Benterki et al. (2019)	116	Chen et al. (2021)	142	Dong et al. (2017)
65	Dou et al. (2016)	91	Izquierdo et al. (2019)	117	Wang et al. (2022a)	143	Izquierdo et al. (2018)
66	Nie et al. (2016)	92	Liu et al. (2019b)	118	Biparva et al. (2022)	144	Deo et al. (2018)
67	Li et al. (2016)	93	Yang et al. (2019b)	119	Zan et al. (2022)	145	Sun et al. (2018)
68	Wu et al. (2016)	94	Rehder et al. (2019)	120	Scheel et al. (2022)	146	Dong and Dolan (2018)
69	Kim et al. (2017)	95	Kruger et al. (2019)	121	Zhang et al. (2022c)	147	Huang et al. (2018b)
70	Vallon et al. (2017)	96	Lee et al. (2019)	122	Syama and Mala (2022)	148	Zhang et al. (2019)
71	Motamedidehkordi et al. (2017)	97	Gu et al. (2020)	123	David and Söffker (2022)	149	Dong et al. (2019)
72	Wissing et al. (2017)	98	Choi and Lee (2021)	124	Griesbach et al. (2022)	150	Xie et al. (2019)
73	Koenig et al. (2017)	99	Mahajan et al. (2020)	125	Ali et al. (2022)	151	Bi et al. (2016)
74	Zheng and Hansen (2017)	100	Du et al. (2020)	126	Do et al. (2023)	152	Xue et al. (2022)
75	Woo et al. (2016)	101	Liu et al. (2020a)	127	Aboah et al. (2023)	153	Dong et al. (2021)
76	Woo et al. (2017)	102	Klitzke et al. (2020)	128	Klein et al. (2023)	154	Zhao et al. (2021a)
77	Díaz-Álvarez et al. (2018)	103	Jin et al. (2020)	129	Sankaranarayanan et al. (2023)	155	Yang et al. (2022)
78	Su et al. (2018)	104	Xu et al. (2021)	130	Li et al. (2023)	156	Liao et al. (2022b)
79	Zhang et al. (2018)	105	Sun et al. (2021)	131	Das et al. (2023)	157	Liao et al. (2023)
80	Deng and Söffker (2018)	106	Zhao et al. (2021b)	132	Khelfa et al. (2023)	158	Hu et al. (2023)
81	Deng et al. (2018)	107	Guo et al. (2021a)	133	Yuan et al. (2023a)	159	Li et al. (2020a)
82	Yuan et al. (2018)	108	Jeong (2021)	134	Zhang et al. (2023)		



(a) Car-following



(b) Lane-changing

Fig. 1. Keyword visualization for the ML-CF and ML-LC papers.

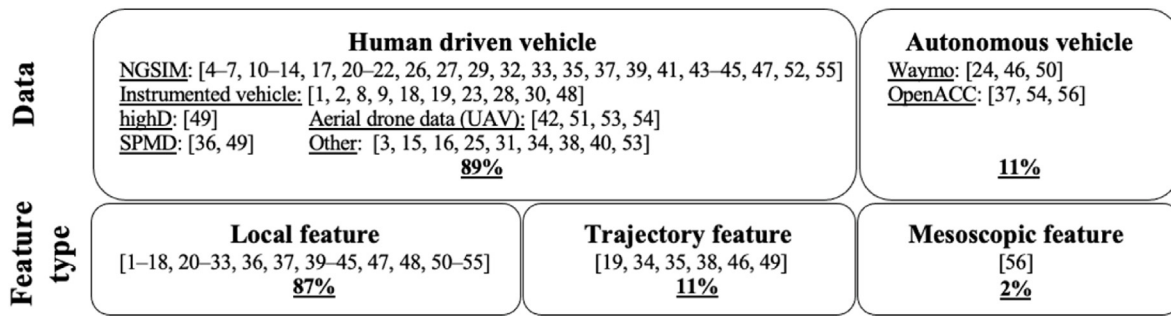


Fig. 2. Breakdown of datasets and input feature types used in the 56 reviewed ML-CF papers.

3.1. ML-CF model features

CF model training strategies that are based on trajectory data fall into two primary categories: microscopic and mesoscopic (or macroscopic) feature training (Li et al., 2020b; Wang et al., 2022b). Mesoscopic feature training entails optimizing mesoscopic traffic patterns predicted by the model against empirical data, such as congestion propagation, stop-and-go, string stability, hysteresis, throughput and capacity. To the best of the authors' knowledge, only one recent study has developed mesoscopic feature training, where mesoscopic oscillation dynamics were explicitly captured through the recursive simulation of a platoon of vehicles (Davies et al., 2024). All other existing studies on ML-CF models have employed microscopic feature training, which can be further subdivided into two variations: local feature training and trajectory feature training.

3.1.1. Local features

The majority of ML-CF models are trained on local features, where the inputs and outputs are considered discontinuous at different time points during training, and the input data are always ground truth. For example, Khodayari et al. (2012) and Zheng et al. (2013) considered only the most recent timestep ($t - 1$) as input data, demonstrating that variable reaction delays improved performance over models with fixed reaction times. More recently, models have evolved to enhance the input feature space, highlighting the importance of including a longer historical trajectory sequence in input data ($t - 1 : t - \Delta t$) (Colombaroni and Fusco, 2014; Zhou et al., 2017). Additionally, these early studies underscore the necessity for model validation via simulation rather than relying solely on discrete predictions from ground truth data, emphasizing that validating models using only a single leader–follower pair is insufficient.

Models trained using microscopic local features are often employed to analyze mesoscopic patterns. For example, Zhou et al. (2017) investigated their model's ability to predict traffic oscillation behavior, Huang et al. (2018a) developed a model to capture discrete driving behaviors, intensity differences, and stop-and-go phenomena, and Wang et al. (2018) investigated their model's ability to recreate the macroscopic fundamental diagram. However, these models are never explicitly trained to optimize their predictions of these mesoscopic metrics, thereby highlighting a disparity between model development and application.

3.1.2. Trajectory features

Despite the popularity of local feature training, compounded errors can arise over time as predicted values are reused when simulating the following behaviors. To address this issue, trajectory feature training aims to optimize continuous following trajectories predicted over time for either an individual leader–follower pair or multiple following vehicles. For example, Sun et al. (2019) fed predicted values back into the model during training to mitigate long-term errors, with training intervals reset using ground truth data to balance accuracy and computational cost. Zhu et al. (2022) developed a seq2seq CF model, where a sequence of outputs was generated from an input sequence of data via an

attention-based transformer with an encoder-decoder architecture, and Raveendran et al. (2022) reused the predicted values in training to develop an LSTM CF model for queue discharge at intersections in the presence of a countdown timer. Although these models help mitigate errors for individual pairs, when simulating multiple vehicles, compounded errors can still propagate as previously predicted following vehicle data are used as leading vehicle inputs for the subsequent vehicle. To mitigate this, Lin et al. (2022) explored a training strategy involving multiple vehicles by adopting a seq2seq LSTM model over a typical seq2seq CF model due to technical challenges within the current ML framework, and Davies et al. (2024) developed a flexible recursive simulation strategy to optimize the trajectories of multiple following vehicles in a platoon.

3.2. ML methods for the ML-CF models

Initially, ANNs emerged as the primary choice for CF modeling, with more sophisticated adaptations such as LSTMs and GRUs gaining traction over time, particularly LSTMs, in recent years. Overall, ANN-based models account for approximately 71% of all the models developed. Recently, these models have been enhanced by techniques such as adversarial learning, seq2seq modeling, attention mechanisms, and hybrid ML-physical methods (ML Physics). Fig. 3 provides a visualization of ML-CF research papers by methodology and year. Some papers may be double-counted if they use multiple methods, such as LSTMs within seq2seq models.

3.2.1. Artificial neural network (ANN) models

ANNs have emerged as the preferred ML-CF method, typically predicting $v_{sv}(t)$ or $a_{sv}(t)$ via immediate historical inputs such as $s_{sv}(t - 1)$, desired speed v_o , leader speed $v_{lv}(t - 1)$, and relative speed $\Delta v_{sv-lv}(t - 1)$ (Chong et al., 2011; Jia et al., 2003; Khodayari et al., 2012; Panwai and Dia, 2007). As the input feature space is expanded to include longer driving sequences ($(t - 1) : (t - \Delta t)$), RNNs, particularly LSTMs and GRUs, are better suited for handling time series data, effectively addressing long-term dependencies and the vanishing gradient problem (Bengio et al., 1994; Géron, 2017). For example, Morton et al. (2017) studied the effectiveness of RNNs in predicting acceleration distributions for CF on highways and evaluating models based on metrics such as negative velocities and gap distances, highlighting that ML-CF models can sometimes predict untenable values, i.e., negative $v_{sv}(t)$ and $s_{sv}(t)$, whereas Ma and Qu (2020) proposed a seq2seq LSTM CF model in an encoder-decoder architecture to generate outputs for 12 future timesteps from 50 historical timestep inputs, highlighting that the accuracy of platoon simulation was improved when additional following vehicles were taken into account by the model. Chen et al. (2023) developed an attention-based NN to predict the SV's attention to the LV and the lane changer at a specific moment (t). Thus, incorporating LC anticipation in CF modeling highlights that the actions of vehicles in adjacent lanes affect CF behavior.

Moreover, LSTMs have gained popularity in modeling AV behaviors.

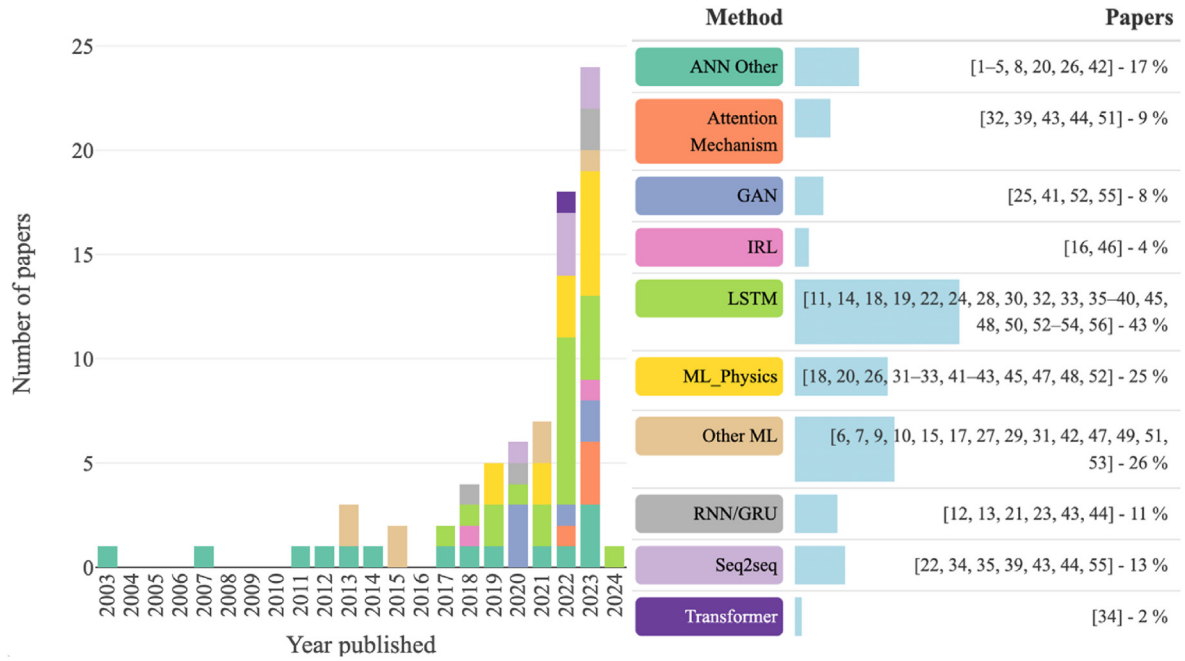


Fig. 3. ML-CF papers published by year and ML method.

For example, Zhou et al. (2022) applied transfer learning with a base model trained on HV data to capture AV driving behaviors from the OpenACC database. Using the same dataset, Davies et al. (2024) captured the oscillatory behavior of a platoon of ACC-controlled vehicles. Making use of the Waymo AV dataset Gu et al. (2020) incorporated front image data into an LSTM, improving CF model accuracy, whereas Adewale and Lee (2023) highlighted key CF behavioral differences between HV-AV and HV-HV pairs.

3.2.2. Hybrid physical model and machine learning methods

Pure ML-based models often lack interpretability and may produce outputs that deviate from expected physical characteristics, such as unrealistic accelerations or negative speeds and following distances (Li et al., 2019; Morton et al., 2017). To address this, researchers have explored hybrid physical models and ML methods. For example, Mo et al. (2021) proposed a physics-informed deep learning (PIDL) model that balances empirical data and physics-based predictions. This approach enables the generation of realistic driver trajectory samples across various uncertainty scenarios. Xu et al. (2022) extended this framework by enhancing the intelligent driver model (IDM) component to accommodate the acceleration of the second following vehicle. Furthermore, the PIDL framework has been applied to account for stochasticity through the addition of a discrepancy term to the GAN loss function (Mo and Di, 2022) or through quantile regression (Liu et al., 2023). Additionally, Zhang et al. (2022b) combined an IDM with a neural process (NP)-based CF model to capture driver stochasticity. The IDM with time-varying parameters captured driver heterogeneity in the CF strategies, whereas the NP model generated realistic behaviors for the observed driving styles. By integrating the IDM parameters and NP parameters, the NP-CF model was able to infer behaviors for unobserved driving styles.

Other hybrid approaches include a weighted sum model, merging LSTM and IDM predictions (Pan et al., 2023), and a physics-informed generative adversarial network (GAN) (Ma et al., 2023), which employs two discriminators to differentiate between empirical and IDM-generated data. This approach shows the ability to generate realistic microscopic trajectories and maintain macroscopic stability during a theoretical simulated 100-vehicle scenario. Additionally, Liao et al. (2022a) and Wang et al. (2023) integrated attention-based networks with IDMs to increase safety and comfort, although it was observed that

nonphysics-based ML models achieved higher speed prediction accuracy (Liao et al., 2022a).

3.2.3. Other machine learning methods

Despite the popularity of ANNs, alternative ML techniques have been employed in the development of CF models. Notably, methods such as locally weighted regression (Papathanasopoulou and Antoniou, 2015), k -nearest neighbors (k -NN) (He et al., 2015), inverse reinforcement learning (IRL) (Gao et al., 2018b), random forest (RF) (Shi et al., 2021), and extreme learning machines (Yan and Zhou, 2021) have been leveraged to model CF behaviors. Furthermore, more advanced adversarial techniques have been explored, such as GANs (Xie et al., 2020), whereas Zhou et al. (2020) integrated generative adversarial imitation learning (GAIL) with a GRU. Yu et al. (2023) developed a fixed-radius near neighbor model, with future research suggesting that the deterministic output could be replaced by a distribution of all potential outputs to create a stochastic ML-CF model to incorporate driver heterogeneity in each prediction.

3.2.4. Comparative research

Zhou et al. (2017) conducted a brief comparative analysis of RNNs based on different output features and concluded that the model predicting $a_{SV}(t)$, was better suited to the CF task than those predicting $v_{SV}(t)$ or $s_{SV}(t)$. A comparative analysis by Kinoshita and Shiomi (2023), including CF models based on a deep neural network, an LSTM network, and one-dimensional and two-dimensional convolutional neural networks (CNNs), indicated that the LSTM model was the most accurate. However, there is a lack of research comparing different ML methods for CF modeling.

To summarize, ML-CF models are typically trained with local features, overlooking broader traffic phenomena, which limits their real-world application in simulations. RNNs, particularly LSTMs, are most commonly used for the CF task because of their strong ability to handle time series data. Moreover, hybrid physical models and ML methods, such as PIDL and physics-informed GANs, have been explored to ensure that outputs conform to physical requirements. Furthermore, most ML-CF models employ deterministic techniques, thereby overlooking stochasticity in driving behavior. The PIDL framework has proven effective in incorporating stochasticity in ML-CF modeling (Liu et al., 2023; Mo et al.,

2021; Mo and Di, 2022; Zhang et al., 2022b). Seq2seq modeling is especially suited to trajectory feature training because of its ability to predict a sequence of outputs that resemble a trajectory. However, the longer the output sequence is, the less accurate it becomes, as it relies on more distant historical inputs. Therefore, unless the prediction of a driving sequence at each iteration is needed, CF models for simulation should use the traditional seq2one architecture. The incorporation of attention mechanisms can increase model accuracy by focusing on crucial parts of the input data. Additionally, as discussed in Section 5.4, visualizing attention weights offers an effective way to enhance model interpretability. Nevertheless, considering the broad range of potential ML methods, training techniques, input and output features, and performance metrics, comparative research is essential to evaluate their respective advantages and disadvantages, which needs further research.

Compared with traditional physical models, ML-CF models demonstrate superiority in replicating trajectories at the microscopic level. For example, the Gipps model outperformed the other models in predicting $s_{SV}(t)$ and $v_{SV}(t)$ (Panwai and Dia, 2007; Papathanasopoulou and Antoniou, 2015), whereas the full velocity difference model and general motors model have also been used for comparison (Shi et al., 2021); however, the most frequently compared model is the IDM (Harth et al., 2021; Yang et al., 2023; Zhou et al., 2017, 2020; Zhu et al., 2022). However, ML models lack theoretical grounding in physical properties, which limits their transferability and interpretability and can sometimes result in physically unrealistic predictions, such as negative $v_{SV}(t)$ or $s_{SV}(t)$, or excessive $a_{SV}(t)$. Moreover, there are no techniques for training ML models that are based on macroscopic traffic features. However, traditional CF models can be calibrated across different scales via various data types, from macroscopic traffic properties derived from loop detector data to microscopic vehicle trajectory data (Kesting and Treiber, 2008; Punzo et al., 2015; Rakha and Gao, 2010; Wang et al., 2024). As a result of these multiscale training options and their interpretable, physical structure, traditional CF models remain widely used in traffic simulation studies (Li and Sun, 2012), including AV studies (Andreotti et al., 2023; Papadoulis et al., 2019) and mixed traffic (Liu et al., 2016).

4. Machine learning-based lane-changing (ML-LC) models

Traditional LC models are typically based on traffic flow theory and involve approaches such as gap acceptance and rule-based methods (Moridpour et al., 2010; Ma and Li, 2023). For example, first proposed by Gipps (1986), rule-based models are the most basic, considering inputs such as desired speed v_0 and gap sizes, where there is a clear causal relationship between explanatory and dependent variables (Ma and Li, 2023). In contrast, ML-LC models are typically nonparametric in nature and are designed to accurately predict local LC behaviors from input sequences comprising a wide range of possible input features. LC behavior is commonly categorized into three processes: LC decision-making (LCD), LC execution (LCE), and LC impact (LCI). LCE modeling has traditionally concentrated on estimating the duration required to complete an LC maneuver (Ali et al., 2021a; Toledo and Zohar, 2007). However, recent developments in ML-LC research have shifted focus toward trajectory prediction during LC (Dong et al., 2021; Hu et al., 2023; Liao et al., 2023; Xue et al., 2022; Yang et al., 2022). This detailed approach to modeling microscopic vehicle behavior is sometimes referred to as trajectory prediction (Ma and Li, 2023; Xue et al., 2022) or lane change implementation (Xie et al., 2019). Given the prominence of trajectory prediction modeling in contemporary ML-LC research, LCE in the current study incorporates the prediction of LC trajectories along with the duration required to complete an LC. Furthermore, this expanded definition highlights the importance of accurately forecasting vehicle movement during the lane change process (Rahman et al., 2013; Zheng, 2014), thereby enhancing the performance of microscopic models employed in traffic simulation studies. Considering these trajectory prediction models, LCE represents a temporal prediction task similar to CF. However, LCE models consider the

influence of vehicles in neighboring lanes on the longitudinal and lateral behaviors of the SV. LCD models focus on predicting when a driver decides to change lanes. Typically, classifier ML methods are employed to distinguish between 'LC' and 'no LC' decisions. Finally, LCI models assess how an LC maneuver affects surrounding traffic in both the current and target lanes (Zheng et al., 2013). Our review suggests that LCD modeling forms the bulk of the ML-LC literature, with fewer models focused on the LCE and LCI.

LC behavior can be further classified into discretionary and mandatory objectives. Discretionary LCs are aimed at improving driving conditions and occur spontaneously. In contrast, mandatory LCs, triggered by factors such as merging or routing requirements, are less common and contingent upon specific environmental factors. These two types of LCs involve different decision-making processes and have various impacts on the surrounding traffic (Zheng, 2014). The reviewed literature demonstrates a strong focus on discretionary LC behavior, with only approximately 16% addressing mandatory LC behavior. LCD models may prioritize early predictions, assessing performance on the basis of the advance time of prediction before the LC occurs (Biparva et al., 2022; Do et al., 2023; Gao et al., 2023; Griesbach et al., 2022; Sankaranarayanan et al., 2023). LCE models predict the detailed behavior of the vehicle changing lanes, often focusing on the lateral and longitudinal positions at each timestep (Deo et al., 2018; Dong and Dolan, 2018; Huang et al., 2018b; Xie et al., 2019; Zhang et al., 2019), although they could also include the start and end times of the LC (Dong et al., 2017). LCI models output both microscopic and macroscopic parameters to assess the impact of LCs on surrounding traffic, such as crash risk and changes in the flow rate (Li et al., 2020a). Fig. 4 presents a breakdown of the data, objectives, and input features used for the development of the ML-LC models.

As with ML-CF models, the most frequently used data source is NGSIM freeway data, whereas no ML-LC models have been developed from AV datasets. The bars in Fig. 5 indicate the percentage of models within each category (LCD, LCE, or LCI) that employed specific features. In this section, we comprehensively review ML-LC models in terms of data, input features, and ML techniques.

4.1. ML-LC model features

The input features used for predicting LC behavior can be broadly categorized into vehicle dynamic features and traffic state features (Ma and Li, 2023).

4.1.1. Vehicle dynamics features

The vehicle dynamic features encompass parameters such as the yaw angle, vehicle speed, acceleration, and following distance of the SV. For example, for LCD, representative vehicle dynamic features are the longitudinal speed v_{SV} , the following distance s_{SV} , and the heading angle of the SV. In terms of the LCE, the longitudinal and lateral positions of the SV, x_{SV} and y_{SV} , are considered the most significant. Some models rely exclusively on vehicle dynamics features to detect LC events. In the reviewed literature, 23%, 10%, and 25% of the LCD, LCE, and LCI models, respectively, employed only subject vehicle dynamics features. For example, to model discretionary LCD, Guo et al. (2021a) proposed an autoencoder neural network that solely utilizes lateral SV movement from the SPMD database. Similarly, on the basis of input features related to the SV and its current leader, Zhao et al. (2021a) developed hidden markov model (HMM)-based LCD and LCE models using the same dataset. Models relying solely on the vehicle dynamics features of the SV can identify an LC only once the SV initiates it. They cannot anticipate which traffic states trigger LC behavior or ascertain acceptable states for drivers intending to change lanes. Hence, additional traffic state features are imperative in model development.

4.1.2. Traffic state features

In contrast to relying solely on vehicle dynamics features, incorpo-

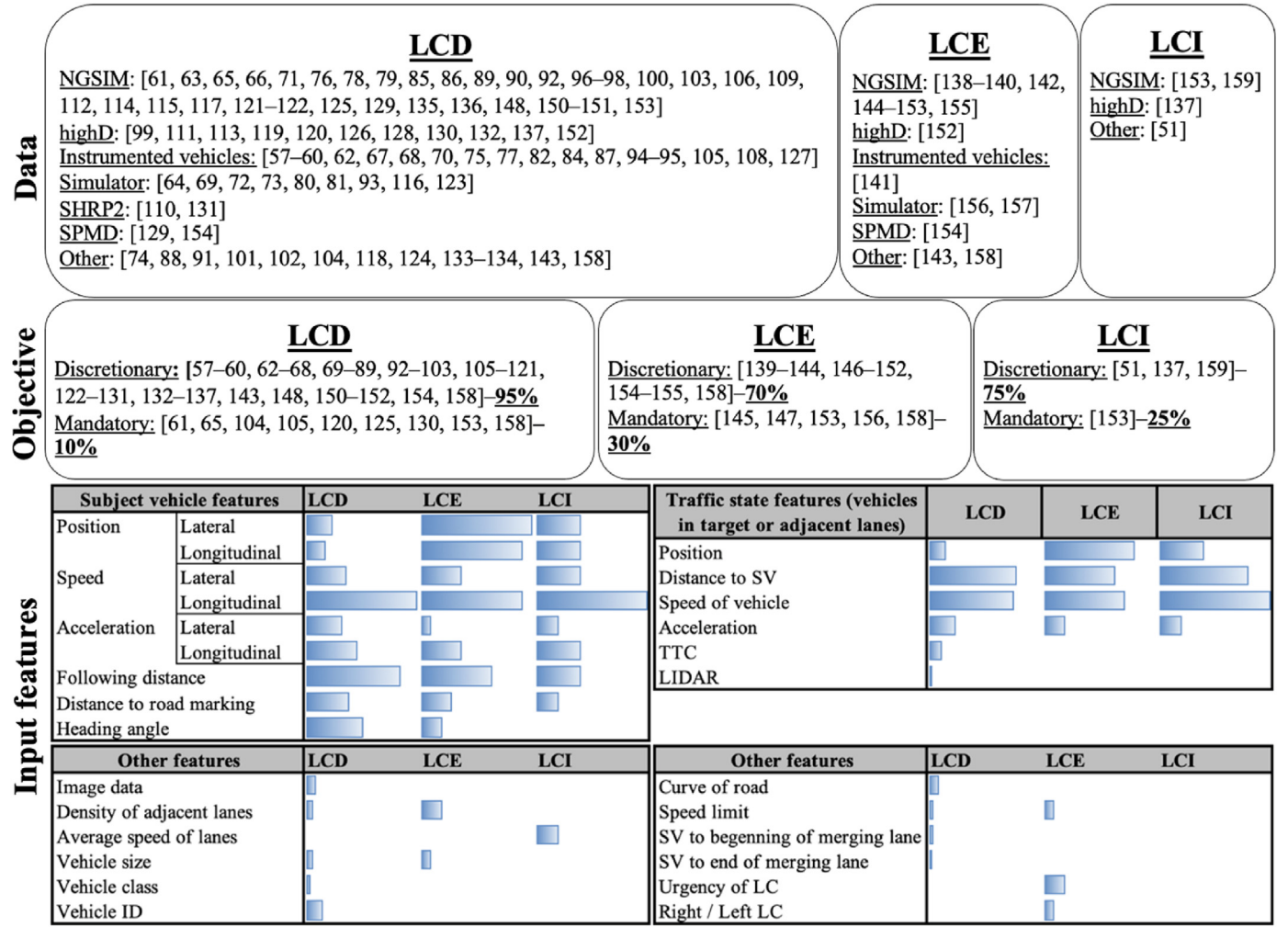


Fig. 4. Breakdown of datasets, objectives, and input features used in the 104 reviewed ML-CF papers.

rating an understanding of traffic conditions can provide deeper insights into potential maneuvers of surrounding traffic, such as cut-ins. Traffic state features, which include relative speeds, accelerations, and distances of surrounding vehicles in adjacent lanes in relation to the SV, are essential. For example, the leading vehicle in the target lane (TL), Δv_{SV-TL} , Δa_{SV-TL} , and s_{SV-TL} , as well as potential gap sizes in adjacent lanes, for example, between the TF and TL vehicles s_{TF-TL} . Moreover, aggregated features such as lane congestion can be inferred from these traffic states, enhancing the predictive accuracy of traffic behaviors (Li et al., 2021; Park et al., 2015; Xue et al., 2022; Zhang et al., 2023). In the reviewed literature, 77%, 90%, and 75% of the LCD, LCE, and LCI models, respectively, include traffic state features in their development. Furthermore, Zhang et al. (2018) and Su et al. (2018) underscored the importance of considering the movements of surrounding vehicles to improve the accuracy and timing of LCD predictions, whereas Díaz-Álvarez et al. (2018) explored LC acceptance, identifying the traffic environments in which drivers are likely to accept an LC. Additionally, Li et al. (2021) leveraged surrounding vehicle motion sequences to evaluate lane congestion levels, thereby informing LSTM and GRU LCD models. Do et al. (2023) devised an LCD model incorporating predicted surrounding vehicle trajectories as inputs, while Gao et al. (2023) employed a dual transformer architecture to link intentions and trajectories for LC prediction, and Huang et al. (2018b) developed a feed-forward neural network (FFNN) and GRU mandatory and discretionary LCE models grounded in social force theory. Moreover, the majority of LCE models

that focus on trajectory prediction adopt a local feature training approach. However, Zhang et al. (2019) introduced trajectory feature training for their LSTM LCE model, observing enhanced accuracy during the LCE task compared with a conventionally trained LSTM model using local features.

4.1.3. Other input features

The identification and prediction of LC behavior can benefit from the inclusion of additional features. For example, video image data captured directly from front-facing cameras mounted on the SV can serve as model input (Biparva et al., 2022; Izquierdo et al., 2019; Wei et al., 2019), thereby incorporating time-related contextual information without explicit trajectory feature inclusion for identifying LC maneuvers. Nevertheless, using image data alone may result in reduced accuracy compared with models incorporating multiple physical input features. Road environment features, albeit less frequently utilized, such as road curvature (Das and Ahmed, 2021; Jeong, 2021; Koenig et al., 2017) and speed limits (Das et al., 2023; Koenig et al., 2017), can also be derived from map information and often complement LC models as supplementary input features. Mandatory LC models may necessitate additional input features to accommodate the urgency of the LC. For example, Hou et al. (2014) and Dou et al. (2016) incorporated features describing the distance from the SV to the beginning of the merge lane, whereas Ali et al. (2022) considered the remaining distance available in the acceleration lane.

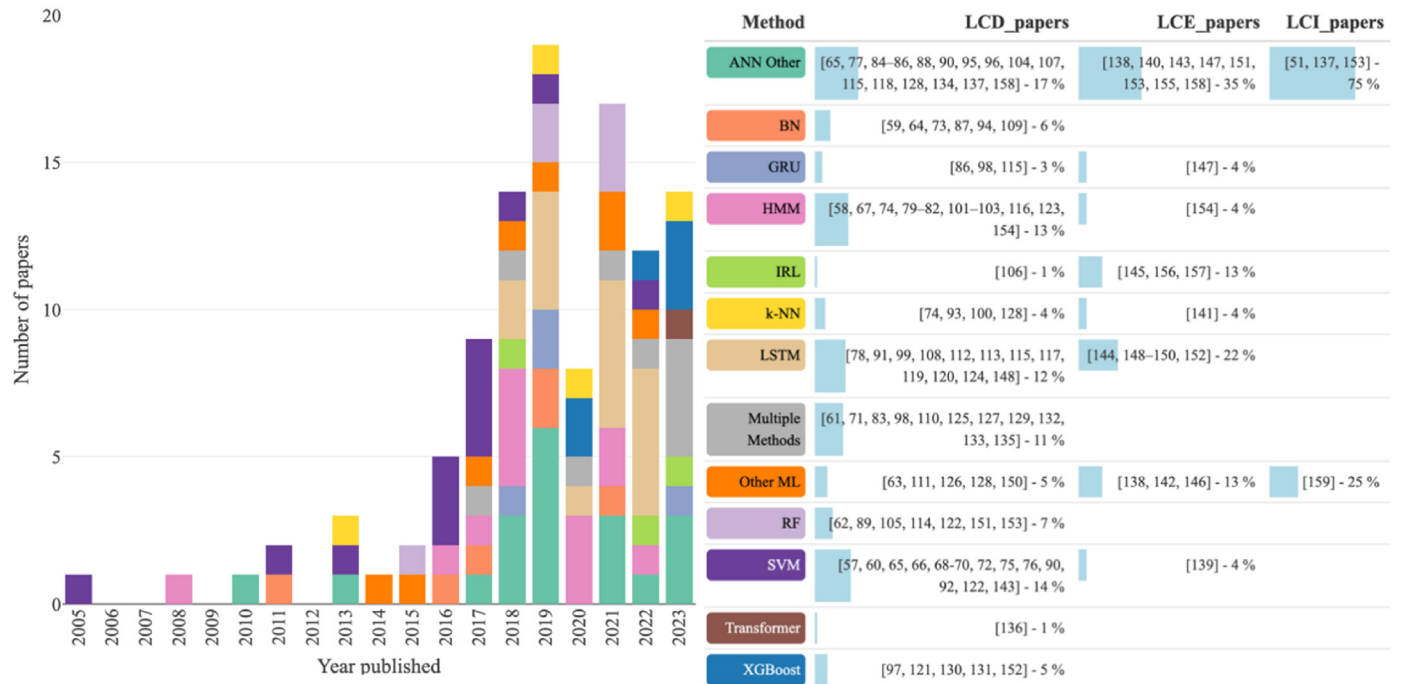


Fig. 5. ML-LC papers published by year and ML method.

4.1.4. Feature selection

LC behavior arises from intricate spatial and temporal interactions involving a multitude of potential input features. Xie et al. (2019) conducted a sensitivity analysis on their deep belief network (DBN) LCD model, revealing that the relative position of the TL was the most critical factor. Furthermore, efforts by Ali et al. (2022) and Li et al. (2023) aimed to increase the interpretability of ML-LCD algorithms by proposing a maximum entropy Shapley additive explanations (SHAP) framework. These findings were consistent with those of (Li et al., 2018; Motamedidehkordi et al., 2017), highlighting that limiting the number of significant features as model inputs often led to improved results. Motamedidehkordi et al. (2017) ranked the importance of different input features via univariate selection with RF. Notably, it was observed that the differential speed between the leading and following vehicles in the current lane one time step prior to the LC maneuver ($\Delta v_{SV-LV}(t-1)$, $\Delta v_{SV-LV}(t-1)$) had the highest contribution to LCD. Zhang et al. (2022c) employed a three-step feature selection process using extreme gradient boosting (XGBoost), which integrates feature importance, metric selection, and recursive feature elimination. Six groups of features were considered, encompassing vehicle dynamic features, surrounding vehicle features, and environmental features. Similarly, Das et al. (2023) utilized Boruta and XGBoost to evaluate feature importance, categorizing features into vehicle kinematics, machine vision, and roadway geometries, with vehicle kinematics emerging as the most influential.

In conclusion, the longitudinal speed and following distance of the SV (v_{SV} and s_{SV}) are the most frequently used vehicle dynamics features. Additionally, inputs related to vehicles in adjacent lanes, such as their speeds and distances to the SV, are often employed as traffic state features. The significant representation of these traffic state features highlights the importance of spatial relationships in modeling LC behaviors. While a wide variety of input features have been examined in research, some studies have shown that focusing on fewer highly influential input features may result in increased model accuracy.

4.2. ML methods for ML-LC models

LCD modeling employs a variety of ML methods, including traditional classifier methods such as support vector machines (SVMs), HMMs, and

RFs, as well as ANN-based models, including LSTMs. In contrast, the LCE and LCI models predominantly utilize ANN-based models. Fig. 5 provides a visual representation of the ML-LC papers published, categorized by specific ML methods across years published, highlighting the diversity of ML techniques employed in LC modeling.

Initially, SVMs emerged as the preferred method, accounting for approximately 50% of all ML-LC models developed before 2018. ANNs, including LSTMs, subsequently gained prominence. Additionally, ensemble methods, categorized under ‘Other ML’, have been employed for LC modeling, exemplified by the XGBoost algorithm. Moreover, owing to the intricacies in predicting LC from high-dimensional input states encompassing multiple surrounding vehicles over time, combinations of ML methods and ensemble models have been employed to increase model accuracy.

4.2.1. Support vector machine (SVM) models

The SVM is a supervised learning algorithm designed for classification tasks that identifies the optimal hyperplane in a high-dimensional feature space that separates data points from different classes (Cortes et al., 1995) and has been extensively employed in various aspects of LC modeling. For example, to capture discretionary LCDs, Liu et al. (2019b) utilized a Bayesian optimization-based SVM, Syama and Mala (2022) integrated SVM with RF models via an LR-based meta-classifier, and Wissing et al. (2017) combined LC probabilities from situational and movement-based SVM models. To model mandatory LCs, Dou et al. (2016) fused SVM- and ANN-based models. Additionally, Tomar et al. (2011) developed an LCE model to predict the trajectory of the SV during discretionary LCs, which exhibited decreased accuracy at higher speeds and could lead to incorrectly predicted collisions.

4.2.2. Hidden markov models (HMMs)

The HMM is a probabilistic model that describes a sequence of observable events generated by an underlying unobservable sequence of states, where the transition between states is governed by probabilistic rules (Rabiner, 1989). For discretionary LCDs, Jin et al. (2020) developed an HMM to establish the relationship between the hidden states (input features) and the observed states (left/right LCs). Zhao et al. (2021a) developed a Gaussian mixture model (GMM)-based HMM to predict

execution times by incorporating CF association and disassociation behaviors. Furthermore, the inherent stochastic functionality of HMMs was leveraged to predict surrounding vehicle cut-ins on freeways to aid ADAS systems (Li et al., 2016; Zhang et al., 2018), whereas Chen et al. (2021) developed a stochastic HMM to predict the LCD of the SV and extended the framework with particle filtering to account for the LCD intentions of surrounding vehicles.

4.2.3. Random forest (RF) models

RF is an ensemble learning method that involves constructing multiple decision trees during training and outputs the mode of the classes of the individual trees as its prediction (Breiman, 2001). Choi and Lee (2021) conducted a comparative analysis of LSTM, RF, GRU, and SVM discretionary LCD models while considering onboard sensor and vehicle-to-vehicle (V2V) feature sets, revealing RF as the best-performing model. They noted that LSTM and the GRU were not optimally suited for classification tasks and might perform better for LCE prediction. Furthermore, Sun et al. (2021) employed RF to predict mandatory LCDs, where the proposed RF model outperformed SVMs and LSTMs.

4.2.4. Bayesian network (BN) models

BNs are probabilistic graphical models that represent a set of variables and their conditional dependencies via a directed graph, enabling inference of probabilistic relationships between variables. Koenig et al. (2017) used a BN to account for the continuous input features and discrete outputs in discretionary LCD modeling. Similarly, Rehder et al. (2016) developed a BN with LR to model discretionary LC dependencies from continuous to discrete nodes generated from a driving simulator. Moreover, Rehder et al. (2019) proposed a hybrid BN and LR LCD model incorporating hidden layers representing the driver's lane contentedness, whereas Song (2021) combined a physical driver model with a BN to predict the probability of discretionary LCDs by surrounding vehicles.

4.2.5. Artificial neural network (ANN)-based models

ANNs have widely been employed for LCD, LCE, and LCI modeling. For example, to capture potential cooperative actions of the following vehicle in the target lane (TF) during an LC maneuver, Bi et al. (2016) introduced cooperative LCD, LCE, and LCI models via the RF and ANN. The ANN LCE model predicted the lateral and longitudinal velocities of the SV and the TF during the LC. The ANN LCE model lacked physical significance or knowledge of the task being performed. Furthermore, Hu et al. (2023) developed a GRU to predict discretionary and mandatory LCDs and an ANN LCE model with hyperparameter optimization capabilities via Bayesian optimization to predict trajectories during left and right LCs. Dong et al. (2021) developed an LCE model for mandatory LCs to assess traffic impacts through simulation. Additionally, Zhang et al. (2023) devised a CNN discretionary LCD model and analyzed the speed and safety impact of the LC on the TF. Lee et al. (2019) incorporated the LC probabilities of surrounding traffic, as predicted by a CNN LCD model, into an optimal velocity CF model to account for CF stochasticity influenced by surrounding vehicle behaviors, thereby also capturing the LCI. This research highlights the need to consider all vehicle behaviors, CF and LC, in holistic or unified driving models.

Furthermore, LSTMs find applications in both LCD and LCE modeling tasks, although they are more commonly employed in the LCE context. For example, Xue et al. (2022) developed LCD and LCE frameworks to account for different traffic environments. The output of the traffic context classification model was used as input in the XGBoost LCD and the LSTM LCE models, thus accounting for different traffic states. To predict discretionary LCDs, Wang et al. (2021) developed a Bayesian inference (BI)-based LSTM. The LSTM captures the decision-making process, and the BI method enables the model to adapt to changes in road and traffic environments. Zan et al. (2022) developed a discretionary LCD model at freeway bottlenecks that included vehicle driving style as an input.

4.2.6. Other machine learning models

Various other ML techniques have been explored for LC prediction tasks, often focusing on aspects such as model combination, ensemble methods, clustering, parameter optimization, reinforcement learning (RL), environment adaptability, and probabilistic modeling. For example, Schlechtriemen et al. (2015) employed a mix of experts (MoE) model, integrating RF and Gaussian mixture regression (GMR) models to predict the probabilities of left and right LCs. Yang et al. (2019b) proposed a time-efficient discretionary LCD model by integrating k -means with k -NN. To improve performance through Bayesian parameter optimization, Gu et al. (2020) combined a deep autoencoder with an XGBoost model. Additionally, Yao et al. (2013) developed a k -NN LCE model, emphasizing the need for testing across different environments and driving scenarios. Moreover, Sun et al. (2018) and Liao et al. (2022b) devised probability-based mandatory LCE models using IRL to select the most likely LC trajectory from a prediction set, whereas Zhao et al. (2021b) developed an RL model to simulate discretionary LCDs inspired by human drivers' decision-making processes. The stochastic nature of DBNs was leveraged to account for driver heterogeneity in LCs by Xie et al. (2019). Finally, Liao et al. (2023) developed a seq2seq LSTM model to select the IRL cost function on the basis of the predicted mandatory LC maneuver and intention, thus accounting for personalized driving behavior.

4.2.7. Comparative research

Given the diverse array of ML methods available, many studies have conducted comparative analyses to identify the most effective approaches for specific prediction tasks. For example, in the context of discretionary LCD modeling, Das and Ahmed (2021) compared multiple models and input feature sets, with XGBoost demonstrating the most reliable and balanced prediction performance across various feature sets. Khelifa et al. (2023) investigated several bagging and stacking ensemble learning metaheuristics, whereas Yuan et al. (2023a) evaluated ML and ensemble models with different input durations, with XGBoost and the light gradient boosting machine (LightGBM) outperforming the LSTM and SVM models. Similarly, Ardakani and Bonds (2023) conducted a comparative analysis of ML and ensemble methods, highlighting the efficacy of ensemble methods, particularly the random undersampling boosted (RUSBoosted) tree model, in addressing class imbalance. Finally, Ali et al. (2022) compared multiple ML methods for both discretionary and mandatory LCD behavior, identifying the extra tree (ET) classifier as the most effective predictor of LC behavior.

To summarize, data preprocessing techniques, including feature selection, Bayesian filtering, and accounting for class imbalance (for example, with SMOTE), are important aspects of LC modeling owing to the complexity of capturing LC behaviors across diverse traffic conditions and the wide range of input features involved. Ensemble methods, such as XGBoost and RUSBoosted trees, demonstrate high efficacy for multiple LC tasks, particularly in handling class imbalance and achieving reliable predictions. RF methods have also shown strong performance for both discretionary and mandatory LCD predictions. RNN-based models are generally better suited for LCE tasks than for LCD classification tasks. For example, LSTM networks excel at capturing temporal dependencies, making them well suited for LCE. HMMs can effectively capture the stochastic characteristics of driving behavior while recognizing temporal data patterns (Li et al., 2016). However, despite the strong predictive capabilities of ML models, integrating them with behaviorally sound frameworks (for example, to account for stochasticity or collision-free criteria) could improve their robustness and interpretability. LCI models that capture the impact of LCs on surrounding traffic typically involve standalone LC and CF models, often comprising ML and traditional approaches (Chen et al., 2023; Lee et al., 2019). Furthermore, research on hybrid physical and ML models is still largely lacking for LC models. As demonstrated in such hybrid models for CF, incorporating physical modeling techniques could increase the robustness of predictions by ensuring adherence to physical characteristics and constraints

and therefore deserves further research for LC models.

Unlike traditional LC models, which were developed on a macroscopic scale to replicate the aggregated behavior of traffic flow (Ali et al., 2023; Ben-Akiva et al., 2006; Kesting et al., 2007), ML-LC models typically predict discrete LC events. Consequently, ML-LC models are rarely compared directly to traditional, flow theory-based models, as this would not be a like-for-like comparison. Traditional LC models are widely used in traffic studies, including AV studies (Papadoulis et al., 2019; Zhong et al., 2020), owing to their simplicity, interpretability, and validation at the macroscopic level. However, this macroscopic approach fails to consider detailed components of LCs, i.e., specific LC events. Performance at both microscopic and macroscopic levels is vital for LC models (Ali et al., 2023). While ML-LC models can account for specific LC events based on surrounding vehicles and traffic context, their highly accurate microscopic nature should be complemented with training and validation at the macroscopic level (Ali et al., 2023) to increase their applicability in traffic simulation studies.

5. Future research directions

This section aims to address the identified challenges in ML-CF and ML-LC model development and propose solutions, with a focus on addressing both models collectively in the following discussion to enable their application in diverse traffic scenarios.

5.1. Model transferability

Generally, ML and data-driven methods are perceived to have a limited ability to generalize to operational domains beyond their training datasets (Chen and Liu, 2016; Han et al., 2022; Wang et al., 2023; Yurtsever et al., 2020). Similarly, our results confirm that the accuracy of the ML-CF and ML-LC models tends to suffer when they are applied in domains not explicitly represented in the training data or where training data are sparse (Gu et al., 2020; Tang et al., 2020; Wang et al., 2018, 2021), making model transferability a significant concern in ML-CF and ML-LC modeling (Hu et al., 2023; Lin et al., 2022; Pan et al., 2023; Scheel et al., 2022; Yan and Zhou, 2021; Zhou et al., 2022). Challenges arise in capturing various driver styles (Gao et al., 2018b; Vallon et al., 2017) and different traffic conditions (Adewale and Lee, 2023; Ding et al., 2013; Harth et al., 2021; Morton et al., 2017; Tomar et al., 2010; Wang et al., 2019). LC behavior exhibits different characteristics at different levels of congestion (Ahmed et al., 2023), limiting its transferability between operational design domains (ODDs) (Adewale and Lee, 2023; Bi et al., 2016; Zhang et al., 2018). Several studies have explored the transferability of models across different datasets or operational contexts, such as highway datasets (Ali et al., 2022; Chen et al., 2023; He et al., 2015; Zhang et al., 2019) or driver profiles (Zhu et al., 2018). Nevertheless, these studies predominantly focus on transferability between similar datasets, often acknowledging the need for further investigation when extending model transferability to more diverse datasets and ODDs. This limitation constrains the effective application of such models in simulation scenarios across heterogeneous traffic environments.

To address these challenges, recent research has proposed a benchmark dataset comprising both HV and AV driving within multiple scenarios and domains, including urban and freeway environments (Chen et al., 2023). However, integrating data from disparate environments and including numerous input variables can introduce biases (Bareinboim and Pearl, 2016) and impact model performance (Ali et al., 2022; Li et al., 2018; Motamedidehkordi et al., 2017; Pearl, 2018). Various advanced ML techniques have been developed to address this issue. Meta-learning (Sun et al., 2023) can enable CF and LC models to quickly generalize to new scenarios with minimal data, such as different traffic densities and road geometries. Domain-invariant representations (Chuang et al., 2020; Nguyen et al., 2021) focus on extracting features relevant to CF or LC that remain consistent across different ODDs, for example, different roads and traffic conditions, enhancing model robustness and generalizability.

Finally, federated transfer learning (FTL) can allow knowledge to be transferred across domains and between datasets (Saha and Ahmad, 2021) by leveraging knowledge from different but related source domains (Liu et al., 2020b).

5.2. Unified driving model (CF and LC)

Our review demonstrates that the behaviors of CF and LC are interdependent (Chen et al., 2023; Lee et al., 2019; Zhang et al., 2022b), both of which rely on interrelated explanatory variables, such as the speeds and following distances of vehicles in current and adjacent lanes ($\Delta v_{SV-LV}(t-1)$, $s_{SV}(t)$, etc.). LCI models, for instance, capture the CF behavioral changes of nearby vehicles that result from LCs, often comprising separate CF and LC model techniques (Bi et al., 2016; Chen et al., 2023; Lee et al., 2019). A prudent next step in microscopic driving modeling is therefore to leverage the nonparametric nature of ML techniques to capture these interrelated behaviors to develop unified driving models. Unified models can seamlessly integrate CF, LCD, LCE, and LCI behaviors into a single driving model, eliminating the need for multiple standalone models.

Many ML techniques can be utilized to achieve unified driving models. For example, multitask learning (Liu et al., 2024; Zhang et al., 2020) involves training a single model to perform multiple related tasks simultaneously, such as predicting both CF behaviors and LC maneuvers concurrently. This approach enables the model to capture dependencies and correlations between the two behaviors, ultimately improving its performance in real-world driving scenarios. Future research should build upon initial multitask approaches developed in the LC field (Yuan et al., 2023b). Moreover, future research could expand on interaction-aware trajectory prediction models for CAVs via LSTMs (Mo et al., 2020), spatial graph convolution networks (Rama and Bajcinca, 2022; Xu et al., 2023), and transformers (Hasan and Huang, 2023). Furthermore, the adoption of these unified models could significantly enhance microscopic ML model utilization within traffic simulations. Future research can build on initial developments, such as Shi et al. (2022), by integrating a trajectory or macroscopic feature training strategy.

5.3. Driver heterogeneity

ML-based microscopic traffic models that have been developed thus far typically train a single model to represent driving behavior, with a limited ability to capture heterogeneous driving behaviors in real-world scenarios. Driver heterogeneity encompasses interdriver differences among various drivers and intradriver variations, reflecting how an individual's behavior can evolve over time or in response to different factors. Recent research (Chen et al., 2024; Zhang et al., 2024) has proposed the use of Bayesian models to capture the heterogeneity and uncertainty of driver behaviors. Future research should further develop ML-based methods for uncertainty quantification to build on traditional models' methods of capturing interdriver heterogeneity. For example, future studies could explore additional types of noise and their impact on different traffic conditions (Laval et al., 2014; Treiber and Kesting, 2017). Researchers could also use ML to advance the understanding of complex stochastic processes, such as geometric Brownian motion and the Langevin equation (Ngoduy et al., 2019; Yuan et al., 2019), to further elucidate the relationship between stochasticity and vehicle dynamics and to understand the varying correlations with vehicle speed.

Additionally, future research should expand on the themes of interdriver heterogeneity by leveraging ML methods to consider more diverse behavioral factors, environmental conditions, and vehicle characteristics. For example, studies could address perception and reaction differences among drivers, as noted by Zheng et al. (2016). The environmental impacts on driver behavior, such as those modeled by Huang et al. (2024) with the Fog-related IDM, could be further investigated under diverse conditions. Moreover, future work could refine models such as the

microsimulation free-flow acceleration model (MFC) by Makridis et al. (2019, 2020) to incorporate more detailed driving styles and vehicle power-train attributes. Unified models can inherently account for the stochastic behavior caused by variations in surrounding traffic, but further efforts to account for driver heterogeneity are still needed (Shi et al., 2022).

5.4. Model interpretability

Our review highlights that the ML-CF and ML-LC models lack interpretability, as they do not provide an identifiable relationship between the diverse input features and outputs. This contrasts with traditional, parametric CF and LC models, which are inherently more interpretable. Furthermore, many ML techniques employed in CF and LC modeling are opaque or ‘black-box’ methods, which present inherent challenges for interpretation, trust, diagnosis, and repair (Pearl, 2018). To address this issue, some research has focused on developing interpretable models. For example, MoE CF models with interpretable templates (Gallitz et al., 2021) and different subsequences during training (Klein et al., 2023). However, their performance may not match that of typical RNNs or MoEs using DNNs, suggesting a trade-off between interpretability and performance. In addition, some CF models utilize attention mechanisms to visualize the derivation of predictions, offering insights into model decision-making processes (Liao et al., 2022a; Zhu et al., 2022). Efforts have been made to enhance interpretability via feature importance frameworks such as SHAP (Ali et al., 2022; Li et al., 2023), which emphasize keeping fewer significant features for improved results. Furthermore, integrating causal inference with Shapley flow could provide better explanations in time series models (Li et al., 2023).

However, several methods have yet to be explored in the literature, including local interpretable model-agnostic explanations (LIME) (ElShawi et al., 2019; Zafar and Khan, 2021), generalized additive models (GAMs) (Machsus et al., 2015), and causal learning (Bareinboim and Pearl, 2016; Pearl, 2018; Scholkopf et al., 2021). LIME can provide insights into why complex CF or LC models make specific predictions for given scenarios, whereas GAMs extend linear models to incorporate nonlinear relationships while maintaining interpretability. Causal learning, on the other hand, can uncover causal relationships between input factors and CF or LC behaviors, thereby enhancing the understanding of driving dynamics. These techniques offer the potential to develop more transparent, flexible, and robust CF or LC models that are interpretable and trustworthy. Furthermore, in the traffic forecasting field, memory augmentation techniques such as memory-augmented conditional neural processes (Wei et al., 2024a) and memory-facilitated joint-space shift adaptation frameworks (Wei et al., 2024b) have been shown to enhance model generalizability across various traffic prediction scenarios and could be adapted for CF and LC models.

5.5. Mesoscopic/macroscopic traffic impact

The primary focus of the ML-CF and ML-LC models developed thus far has been on replicating microscopic phenomena, such as vehicle trajectories and individual lane change decisions. However, macroscopic training and validation approaches are completely lacking in the literature. However, CF and LC models are frequently used to analyze mesoscopic or macroscopic traffic phenomena, such as the dynamics of traffic oscillations (Morton et al., 2017; Zhou et al., 2017), stability (Ma et al., 2023), hysteresis (Pan et al., 2023), platoon length (Liu et al., 2023), and flow/density relationships (Qin et al., 2023). Unlike traditional CF and LC models, which are capable of capturing microscopic (Punzo et al., 2021), mesoscopic (Vasconcelos et al., 2014), or hybrid behavior (Zheng et al., 2023) in model calibration and are thus commonly used in flow-based simulation studies, the training of mesoscopic features remains largely unexplored in ML model development. A recent study (Davies et al., 2024) focused on multiscale training approaches targeting

mesoscopic patterns during oscillations. However, to analyze a broad spectrum of mesoscopic or macroscopic traffic impacts effectively and enhance the deployment of ML-CF and ML-LC models in microscopic traffic simulations, continued advancements in ML training methods are necessary (Zheng, 2014).

In trajectory prediction models, particularly CF and LCE, the flexible recursive simulation of multiple vehicles within the loss function, similar to that first proposed by Davies et al. (2024), is a necessary step toward quantifying and optimizing mesoscopic metrics, as mesoscopic patterns naturally emerge from the interactions between multiple vehicles. However, relying solely on mesoscopic feature training may yield sub-optimal results, as it addresses only the qualitative likeness between simulated and observed data (Li et al., 2020b). Therefore, it is recommended that both microscopic trajectory and mesoscopic features be integrated in a multiscale training framework to increase simulation accuracy and strengthen the link between model development and real-world application. However, the recursive simulation of multiple vehicles within the training function is expected to be computationally expensive and more challenging for model training. One potential solution to this challenge could involve initially training the model in the standard way, leveraging the faster local feature training method. This pretrained model serves as an accurate starting point from which more demanding and complicated multiscale training can commence. Further training could then be accomplished via fine-tuning, transfer learning, or FTL. Another challenge lies in the calculation of mesoscopic metrics within the ML framework, as these metrics must be explicitly derived directly from the model's output via differentiable functions to enable backpropagation via gradient descent (Géron, 2017). This requirement imposes limitations on what mesoscopic metrics can be incorporated into the model's training. A possible solution to this challenge could involve leveraging implicit RNNs (Sanokowski, 2020) and implicit differentiation (Bolte et al., 2021) to enable the calculation of diverse traffic patterns within model training.

5.6. Physical constraints in model training

Our review highlights that a key difference between traditional and ML-based CF and LC models is the predefined, physics-based structure of traditional models. Consequently, ML-based models lack awareness of their purpose or application, operating without consideration of fundamental physical principles and rules governing real-world vehicle behavior, which can lead to predictions that result in unrealistic physical states or crashes such as negative $v_{SV}(t)$ or $s_{SV}(t)$, or excessive $a_{SV}(t)$ (Khelfa et al., 2023; Morton et al., 2017), indicating a potential issue in the field (Lin et al., 2022; Soldevila et al., 2021; Tomar et al., 2011). Research has explored hybrid physical models and ML methods, such as PIDL (Liu et al., 2023; Mo et al., 2021; Xu et al., 2022). Alternatively, a simpler solution could involve integrating physical constraints directly into model training. These constraints can be implemented in two ways: soft constraints and hard constraints (Pan, 2021). Soft constraints are enforced by adding additional penalties to the loss function, whereas hard constraints impose conditions that must be satisfied during model generation.

Hard-constrained ML models offer robustness and accuracy; however, optimization can be challenging. Examples of hard-constrained models in other domains include incorporating constraints into the model architecture or loss function (Beucler et al., 2021; Márquez-Neila et al., 2017). Soft constraints could involve penalizing the model during training if it generates outputs leading to negative velocities, improper following distances, or accelerations outside acceptable ranges. Safety-related features, such as time to collision (TTC), could also be integrated into the model's development to ensure safer ML models. However, incorporating constraints into model training poses challenges, particularly with the commonly used local feature training approach, which may not effectively address physically implausible outcomes on the basis of a single future prediction from ground truth data. To overcome this

limitation, a recursive training strategy that captures the interdependencies between multiple vehicles over time would enhance the effectiveness of these constraints.

5.7. ML models for AVs

Current research on AV traffic impact often relies on traditional CF and LC models to analyze throughput variations under varying AV market penetration rates (Abdulsattar et al., 2020; Andreotti et al., 2023; Gueriau and Dusparic, 2020). However, these studies often entail assumptions regarding AV driving behaviors (Do et al., 2019; Gora et al., 2020; Hörl et al., 2016; Narayanan et al., 2020), such as conservative following distances when a CAV is following an HV and more aggressive following distances when CAVs are following other CAVs because of possible communication between the vehicles. To remove these assumptions and create realistic simulations based on real-world AV trials, ML techniques have emerged as a viable approach for learning CF and LC behaviors from AV trial data (Caesar et al., 2020; Gunter et al., 2020, 2021; Houston et al., 2020; Makridis et al., 2021; Sun et al., 2020).

Future research should explore ML models for cooperative LCs in connected and autonomous vehicles (CAVs) (Bi et al., 2016; Hidas, 2005; Wei et al., 2013) once empirical data on cooperative LCs become available. For example, the integration of ML approaches (Guo et al., 2021b; Wang et al., 2022c) with game theory methods (Ali et al., 2019, 2021b) holds promise for modeling LCs in a connected environment. Furthermore, to accommodate evolving driving behaviors and data transfer facilitated by vehicle-to-everything (V2X) communications in a distributed manner, federated learning (FL) could be a viable approach. FL leverages multiple datasets to collaboratively train models without the need to centralize vast amounts of data. It has already been applied across various areas of AV modeling (Chellapandi et al., 2024), including AV driving (Nguyen et al., 2022; Zhang et al., 2021). Through real-time

information exchange on road conditions, traffic flow, and nearby vehicles, FL can empower models to adapt and incorporate contextual information into their predictions of driving behavior, resulting in more accurate and context-aware driving behaviors in simulations. Furthermore, by embedding human-like semantic understanding into these models, AVs can achieve more accurate and context-aware predictions of human driving behaviors, thereby improving safety and efficiency in mixed traffic environments (Xia et al., 2023a).

5.8. ML model application beyond traffic analysis

The ML-CF and ML-LC models also offer promising applications that extend beyond traditional traffic analysis. For example, their high level of microscopic accuracy makes them valuable for generating synthetic traffic data, which can be used to enhance scenario testing, train autonomous vehicle (AV) systems (Feng et al., 2023), and evaluate traffic management strategies under diverse conditions (Nigam and Srivastava, 2023). Additionally, these models can be applied in data imputation (Laña et al., 2018) and fill in missing information from incomplete traffic datasets or sensor failures, which is essential for real-time traffic monitoring and forecasting. Additionally, ML-CF and ML-LC models could contribute to ML-based spatiotemporal prediction and anomaly detection frameworks (Fosić et al., 2023), identifying unusual traffic patterns or incidents in real time, for example, unusual LCs or braking and acceleration, which would support more effective incident response and traffic flow management.

Unified ML-CF and ML-LC models, capable of accounting for all vehicle behaviors, could be developed for the safety testing of AVs (Feng et al., 2021) or to evaluate the safety implications of infrastructure interventions, overcoming the limitations of traditional models in safety-critical scenarios owing to their simplistic, inherently safe structure. Moreover, ML-CF and ML-LC models are underutilized in emissions

Table 3

Summary of the main gaps and future research directions of ML-CF and ML-LC modeling techniques.

Strength	Limitation	Future recommendation
- Enhanced prediction accuracy: ML algorithms can handle nonlinear relationships and interactions between variables, leading to more accurate predictions of vehicle behavior in diverse traffic conditions. - Reduced assumptions: Traditional models often rely on predefined assumptions about driver behavior and traffic flow, which may not always hold true in diverse real-world scenarios. ML models can learn patterns directly from data without relying on such assumptions. - Capture of complex Interactions: ML methods can capture complex interactions between many variables that might be challenging to incorporate in traditional approaches. - Adaptability and flexibility: ML models can be easily updated and retrained as new data becomes available, allowing them to adapt to changing traffic patterns, road conditions, and driver behaviors over time.	Generalizability: ML models exhibit poor generalization to operational domains outside of their training. Interpretability: ML models exhibit poor interpretability. It can be difficult to trust and validate their use in diverse application scenarios. Calibration: limited ML model training approaches due to restrictions in backpropagation requirements. This results in a lack of model training to capture mesoscopic and macroscopic traffic phenomena. Physical awareness: ML methodologies do not incorporate physical knowledge within model training and could erroneously predict unsafe or unrealistic situations. Research gap Limited research capturing heterogeneous driving behavior in real-world scenarios. Develop unified CF and LC model to predict integrated microscopic driving behavior. ML models could be further developed to account for cooperative behavior from V2X communications.	- Incorporate additional input features capable of accounting for changes in operational domain. - Meta-learning. - Domain-invariant representations. - Federated transfer learning. - Causal learning. - LIME. - GAM. - Other techniques: feature selection, SHAP analysis. - Integrate recursive training strategy involving multiple vehicles. - Employ fine-tuning or transfer learning strategy to optimize recursive training strategy to capture dynamics between multiple vehicles. - Quantify and optimize mesoscopic metrics that emerge from the simulation of multiple vehicles. - Include physical and safety-based constraints in model training. - Recursive simulation training strategy is a prerequisite for the above, as physically untenable predictions are more likely to occur from multiple vehicle interactions. Future recommendation - Investigate Bayesian modeling techniques. - Integrate geometric Brownian motion and the Langevin equation in ML modeling. - Leverage nonparametric nature of ML methods to include multiple relevant input features for the required prediction tasks. - Explore ensemble modeling methods for diverse modeling tasks. - Multitask learning. - Federated learning methods. - Integrated ML and game-theory approaches.

studies; by simulating detailed vehicle interactions, these models can enhance existing emissions modeling (Xia et al., 2023b), enabling more accurate estimation of emissions under different traffic conditions, thereby assisting in environmental impact assessments. These models also hold potential for studying other modes of transport, such as cycling and e-scooters. For example, by incorporating new data sources (Schumann et al., 2023), they could be adapted to study detailed interactions between vehicles, cyclists and e-scooters to expand on existing research (Distefano et al., 2024) in supporting micromobility planning. Together, these applications highlight the versatility of ML-based CF and LC models across a variety of fields.

6. Conclusions

This study provides the first systematic review of machine learning (ML)-based approaches for car-following (CF) and lane-changing (LC) models, identifies critical research gaps, and proposes future research directions. Table 3 summarizes the key findings, including the strengths, limitations, and recommended research directions, aimed at enhancing the interpretability, transferability, and robustness of machine learning-based microscopic traffic flow models and simulations.

To summarize, ML-based CF and LC models present many strengths, including enhanced prediction accuracy, reduced assumptions, the ability to capture complex interactions, adaptability and flexibility. However, several challenges persist, including poor generalizability and interpretability, nonconformance to physical constraints, and inadequate methods for mesoscopic and macroscopic training methods to capture broader traffic phenomena. To address these challenges, future research should explore advanced techniques, including meta-learning, domain-invariant representations, and causal learning, to improve model generalizability and interpretability. Furthermore, recursive training strategies, which incorporate physical constraints and optimize mesoscopic metrics, are critical for improving model calibration and ensuring realistic predictions. The integration of cooperative behaviors via V2X communications and leveraging advanced techniques such as federated learning and multitask learning can further enhance the robustness and applicability of these models in diverse, real-world traffic scenarios.

Our research offers valuable insights to both the transport and machine learning communities by demonstrating the advanced capabilities of machine learning techniques in tackling key challenges in microscopic car-following and lane-changing models. As machine learning continues to rapidly advance and diversify, our work can serve as a bridge between the computer science and transport communities, contributing to the creation of more robust, reliable, and interpretable models and simulations and ultimately enhancing scenario testing and optimization for traffic engineers, urban planners, and developers of autonomous driving technologies.

Data access statement

This study is based solely on a review of existing literature and does not involve the collection or generation of new datasets. All sources referenced in this paper are publicly available and have been appropriately cited. No additional data were created or analysed beyond those presented in the referenced works.

CRedit authorship contribution statement

Davies Rowan: Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Haitao He:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Fang Hui:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Ali Yasir:** Writing – review & editing, Methodology, Conceptualization. **Quddus Mohammed:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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